

**Unobserved Heterogeneity:
Evidence and Implications for SMEs' Hedging Behavior**

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Practitioner's Abstract

Financial research indicates that several firm characteristics are related to the use of derivatives. Less attention has been paid to the role of the characteristics of managers, which are particularly important when studying derivative usage of small and medium sized enterprises (SMEs). In this paper we focus on the influence of manager's level of education, the manager's decision-making unit, and the fundamental determinants of risk management — managerial risk attitude and managerial risk perception — on SMEs' commodity derivative usage. In empirical studies to date, the heterogeneity of derivative users has been neglected. We propose a generalized mixture regression model that estimates the relationship between commodity derivative usage and a set of explanatory variables across segments of an industry. Accounting for unobserved heterogeneity reveals that segments of the industry have different determinants of derivative use. Moreover, the heterogeneity at the segment level appears to mask significant effects at the aggregate level, most notably the effects of risk attitude and risk perception.

Key words

Decision-Making Unit; Derivatives Usage; Hedging Behavior; Unobserved Heterogeneity; Marketing Channel; Mixture Regression Model; Segments; Small and Medium Sized Enterprises)

Introduction

Financial derivatives such as futures and options provide managers with tools to manage price risk. Derivative exchanges and financial institutions through over-the-counter trading facilitate the exchange of these instruments. Recently the competition among financial institutions that provide these services has increased, leading to the development of customized financial products to better fulfill users' needs. Accordingly, the interest of financial institutions in identifying the motivation behind derivative usage by different groups of (potential) users has increased (e.g., Angel, Gastineau, and Weber 1997; Fridson 1992; Nesbitt and Reynolds 1997).

Géczy, Minton, and Schrand (1997); Koski and Pontiff (1999); Lee and Hoyt (1997); Mian (1996); Nance, Smith, and Smithson (1993); and Tufano (1996), among others, have conducted research on the determinants of derivative use. These studies have assumed, often unrealistically, that enterprises' motivations for using derivatives as a hedging tool are homogenous. However, firms from different regions or of different organizational structures may face dissimilar economic constraints and conditions that can lead to different derivative choices. Similarly, managers from different segments of an industry may possess dissimilar objectives and motivations that also can result in different derivative decisions. Consequently, we might expect the factors that influence a firm's financial instrument choice to vary across segments of an

industry, and that common factors may influence firms differently. Clearly, this heterogeneity impacts the efforts of financial institutions in developing appropriate derivatives, particularly for customized products.

Here, we model the effects of (unobserved) heterogeneity on the determinants of firms' derivative usage. We present a generalized linear mixture model that simultaneously investigates the determinants of derivative usage, and allows for the possibility of unobservable segments in the population that may possess different determinants of derivative usage. We demonstrate how managers behave differently regarding financial derivative usage, and show the importance for financial institutions to develop an understanding of their customers.

In contrast to previous work, we study the derivative usage by managers of small and medium-sized enterprises (SMEs). SMEs do not have different departments nor do they have separate organizational structures to administer functions such as research & development, manufacturing-quality control, and sales and accounting. The management of these functions is combined within the (owner-) manager. Moreover, the ownership of SMEs is often concentrated. In such a structure, the (owner-) manager's risk aversion can provide an important motivation to manage risk (Mayers and Smith 1982; Smith 1995). The wealth of the manager is directly affected by the variance of the SME's expected profit, constituting a (extra) motivation to consider hedging (Smith and Stulz 1985).¹ SME's also differ from large corporations in their capital structure as bondholders are relatively scarce. Avery and Bostic (1998); and Berger and Udell (1998) show that private equity, bank loans and personal commitments dominate the capital structure of SMEs. These differences are the rationale for including manager's, along with firm's, characteristics in the investigation of the determinants of derivative usage.

In this paper we exclusively focus on derivative usage for reducing price risk when buying inputs and selling outputs, and thus do not consider hedging motivated by risky investment projects. Our empirical investigation is in the raw food industry and as such derivative use refers to *commodity* derivative usage. We pay special attention to the fundamental motivation behind derivative usage as a hedging tool: risk attitude, risk perception and their interaction. Although these factors are recognized in theory as being crucial for understanding derivative usage, to date risk attitudes and risk perceptions rarely appear in empirical studies of derivative usage. Their absence primarily is explained by two reasons. First, most studies focus on large corporations rather than their managers and thus concentrate on firm characteristics. Second, risk attitudes and risk perceptions are not directly observable and cannot be obtained from accounting data. Measuring these concepts in a realistic and accurate manner is a difficult task. Here, we measure risk attitudes of 415 SMEs in a relevant economic business setting using computer-guided interviews and an experimental design based on the expected utility model.

Determinants of Derivative Usage as a Hedging Tool

Several factors have been identified to explain why firms use derivatives as a hedging tool. We provide a brief overview of the primary determinants of derivative usage, concentrating on the

¹ This is consistent with the notion that firms whose portfolios are poorly diversified have stronger incentives to hedge (Smith 1995).

use of (commodity) derivatives as a means to reduce SME's input and output price risk. Particular attention is given to the "fundamental determinants" behind risk management and the use of derivatives: risk attitude and risk perception. We first discuss the influence of managers' risk attitude and risk perception on derivative use, as well as the manager's education level, followed by the characteristics of the firm.

Managers' Characteristics Influencing Derivative Usage

We expect *Risk Attitude (RA)* to be an important determinant of a SME manager's market behavior. Risk aversion refers to a preference for a guaranteed outcome over a probabilistic one of equal value; risk-taking implies the opposite. Risk attitude ranges from extremely risk-averse to extremely risk-seeking. Risk-averse managers are willing to take risks, but must be compensated for assuming the risk. A risky asset must yield an expected return high enough (compared to a risk-free return) to compensate the risk-averse managers for accepting the risk. Risk-seeking managers will engage in risky (speculative) behavior or seek out ways to increase their risk. When managers are risk-neutral they will not engage in any risk management. Recently Tufano (1996) has found that managerial risk aversion affects corporate risk management policy in the North American gold mining industry. We expect a positive relationship between risk aversion and the use of derivatives.²

Risk must first be perceived before a manager is able to respond to it. *Risk Perception (RP)* may be defined as a manager's assessment of the risk inherent in a situation. While a market might be considered turbulent by economic standards, the level of risk it presents will depend on the manager's risk perception. A manager that can predict the market price will perceive the market as less risky, and take fewer steps to reduce risk. We expect a positive relationship between risk perception and the use of derivatives.

Only when managers of SMEs perceive risk and are risk-averse will they show risk management behavior, that is, derivative usage. In a hedging context, risk-seeking managers who perceive risk, and risk-neutral managers will not engage in derivative usage. Moreover, when managers perceive no risk, risk attitude will have no influence on behavior. Thus risk perception is linked to actual behavior by means of the manager's risk attitude. The effect of risk attitude on derivative usage will be larger the more (less) risk the risk-averse (risk-seeking) manager perceives. Consequently, we expect the *interaction between risk perception and risk attitude (RP*RA)* to be a primary determinant of derivative use.

Owner-managers of SMEs often perceive derivatives as providing a complex financial service, which inhibits participation in derivative trading (Glaum and Belk 1992). Costs associated with using derivatives include information gathering and the efficiency of their adoption. The level of *Education (EDU)* is related inversely to the cost of information gathering

² Working (1953) challenged the idea that risk reduction is a main driver behind hedging. In his view, hedging was primarily a sort of arbitrage, to be engaged in only when the hedger perceived a promising opportunity for profit. In later work Working recant his earlier position (1962). The adoption of the portfolio theory approach in the 1960's to decisions in futures markets sets risk in the center of why one should hedge (e.g., Stein 1961; Johnson 1960).

and efficiency of using derivatives as it increases the ability of the manager to assimilate new ideas and analyze changing situations. We expect the level of education to be positively related to manager's use of derivatives.

Firms' Characteristics Influencing Derivative Usage

Related to risk perception but conceptually different is the notion of risk exposure. When a firm trades daily in a risky market its *Risk Exposure (RE)* will be smaller than a firm that enters the market on a monthly basis, although both firms might perceive the market as equally risky. Several researchers have empirically identified the relationship between the degree of risk exposure and use of derivatives. Géczy, Minton, and Schrand (1997), in a study of the use of currency derivatives, find that firms with extensive foreign exchange-rate exposure are more likely to use currency derivatives. Carter and Sinkey (1998) in a study of the use of interest-rate derivatives by U.S. commercial banks find that the use of derivatives is positively related to interest-rate risk exposure as measured by the absolute value of the 12-month maturity gap.³ We expect a positive relationship between risk exposure and the use of derivatives.

The expected costs of a firm's financial distress increase with an increased probability of the firm's insolvency. A firm with a higher probability of insolvency would benefit from a decrease in the variance of firm value. Therefore firms with a relative high leverage (*LEV*) (high debt-to-asset ratio) are more likely to use derivatives to reduce risk than firms with a relative low leverage. Nance, Smith, and Smithson (1993); and Turvey and Baker (1990) identified this relationship between leverage and derivative usage. Hentschel and Kothari (1995) also find that leverage is highly positively correlated with derivative usage. Thus, we expect a positive relationship between leverage and the use of derivatives.

Another important factor that influences derivative use is the *Size of the Firm (SF)*. Larger firms are believed to participate in derivatives more actively because of informational economies and economies of scale. Moreover, larger firms are more likely to have the necessary resources and potential trading volume to warrant the use of derivatives (Nance, Smith, and Smithson 1993). Géczy, Minton, and Schrand (1997) argue that firms with the greatest economies of scales in implementing and maintaining a risk management program are more likely to use (currency) derivatives. Mian (1996); and Carter and Sinkey (1998) find evidence for a positive relationship between a firm's decision to participate in derivative contracts and its size. Furthermore, Block and Gallagher (1986) determine for general corporations that informational economies or economies of scale were positively related to derivatives use.⁴ We expect a positive relationship between firm size and the use of derivatives.

³ In a related context, Schrand and Unal (1998) provide an explanation for hedging as a means of allocating rather than reducing risk. They argue that, when increases in total risk are costly, firms optimally allocate risk by reducing (increasing) exposure to risks that provide zero (positive) economic rents.

⁴ Arguments also have been formulated for a negative relationship between firm size and hedging activity (see, for example Nance, Smith, and Smithson 1993). However, the weight of the evidence is most consistent with the discussion in the text.

The Decision-Making Unit and Derivative Users Heterogeneity

To our knowledge the influence of the decision-making unit of managers of SME on derivative usage, and the implications of unobserved heterogeneity among derivatives users have not been addressed in literature. First, we elaborate on the SME's decision-making unit, after which we discuss the implications of unobserved heterogeneity in understanding the determinants of derivative usage.

The management functions of SMEs are commonly performed by the owner-manager. While the owner-manager is the primary decision-maker, the decision to use derivatives is often influenced by advisors, employees and other important people. These people form the SME's Decision-Making Unit (DMU). Recent findings suggest that the DMU has a significant effect on firms making major decisions (Dholakia et al. 1993). Various members of the SME may be involved in the SMEs decisions. The SMEs' employees, particularly those responsible for financial decisions, and who may experience directly or indirectly the consequences of using derivatives, may be motivated to get involved in the decision about the extent of derivative usage.⁵ Individuals external to the SME also may have influence on the decision to use derivatives. SMEs use advisors, such as consultants or bank account managers in order to optimize their decision-making process regarding the use of derivatives. We expect that the opinion of these individuals, who are important to the manager when derivatives are concerned, will influence the SME's use of derivatives.

In work to date on the determinants of derivative usage a single set of parameters is estimated for a set of explanatory variables under the assumption that all firms face similar constraints and behave in similar ways. A potential problem with this approach is that standard regression neglects the integer properties of the dependent variable (e.g. use of derivatives), not allowing for the presence of segments or clusters in the population (Morduch and Stern 1997). The assumption that all observations can be characterized by a single model is convenient but can mask critical relationships. Factors, which play an important role in derivative usage for a particular segment of an industry, may be inconsequential for other segments. Further, estimating a model across the entire sample may be potentially misleading if the sample consists of a number of unknown segments, in which the relationships of derivative use differs. This situation requires disaggregation of the sample into segments. In this study, we use a generalized linear mixture likelihood approach that is able to simultaneously identify unobserved segments, and to estimate the relationship of SME's and manager's characteristics with derivatives use in each of these segments.

Model

One way to deal with heterogeneity is first to form groups a priori and then use a standard regression analysis within these groups to gain insight into the factors influencing the usage of derivatives. Two problems might arise. It might be difficult a priori to determine which variables should be used to segment the population. Second, a priori segmentation of the total sample

⁵ We do not study the decision-making process within a DMU, rather we are interested in the effect that members of the DMU have on the manager's decision to use derivatives.

based on some variables chosen by the researcher may be infeasible or insufficient to explain differences in derivative usage. Hence, we propose a modeling procedure where a priori knowledge about the number of segments and the factors that account for heterogeneity is not needed, but rather inferred from the data.

Our procedure is a generalized mixture model. In mixture models it is assumed that a sample of observations arises from a specified number of underlying populations of unknown proportions. A specific form of the density of the observations in each of the underlying populations is specified, and the mixture approach decomposes the sample into its components.⁶ Recently, conditional mixture models have been developed that allow for the simultaneous probabilistic classification of observations and the estimation of regression models relating covariates to the expectations of the dependent variable within unobserved (latent) segments. DeSarbo and Cron (1988) propose a conditional mixture model that enables the estimation of separate regression functions and corresponding membership in a number of segments using maximum likelihood. In this paper we use a generalized linear regression mixture model first formulated by Wedel and DeSarbo (1995). This approach allows us to simultaneously estimate the probabilistic classification of the SMEs by their derivative use, and to explain derivative use by a set of explanatory variables in each segment.

Assume that the measures on derivative usage are indexed by $k = 1, \dots, K$ for $j = 1, \dots, J$ SMEs. The measurements are denoted by y_{jk} . We assume that the SMEs come from a population that is composed of a mixture of S unobserved segments, with relative sizes $\mathbf{p}_1, \dots, \mathbf{p}_S$ and that $\mathbf{p}_s > 0$ and $\sum_{s=1}^S \mathbf{p}_s = 1$. The distribution of y_{jk} , given that the SME j comes from segment s , is from the exponential family of distributions and is denoted as $f_{jk|s}(y_{jk})$.⁷ Given segment s the expectation of the y_{jk} are denoted as \mathbf{J}_{sjk} . Within segments, these expectations are modeled as a function of our set of P ($p = 1, \dots, P$) explanatory variables $x_{1, \dots, x}$ and the parameter vector \mathbf{b}_{ps} in segment s :

$$(1) \quad g(\mathbf{J}_{sjk}) = \sum_{p=1}^P x_{jpk} \mathbf{b}_{ps}$$

where $g(\cdot)$ is the link function which links the expectations of the measurements to the explanatory variables. Since our dependent variable consists of counts of the number of derivatives used (i.e. the notional value of these derivatives), we use a Poisson mixture regression model (e.g., Bockenholt 1999; Gurmu, Rilstone, and Stern 1999). For the Poisson mixture, the conditional probability function of y_{jk} , given that y_{jk} comes from segment s , is:

⁶ The development of mixture models dates back to Newcomb (1886) and Pearson (1894). For a detailed review on mixture models, see Everitt and Hand (1981); Langeheine and Rost (1988); McLachlan and Basford (1988); Titterton, Smith, and Makov (1985); and Wedel and Kamakura (1998).

⁷ The exponential family includes the binomial, Poisson, and gamma distributions.

$$(2) \quad f_{jk/s}(y_{sk} / \mathbf{J}_{sjk}) = \exp[y_{jk} \mathbf{J}_{sjk} - \exp(\mathbf{J}_{sjk}) - \log(y_{sk})]$$

with the link function $g(\cdot) = \log(\cdot)$. Because in our empirical study we use a single measure to measure derivative usage $K = 1$.

The unconditional probability density function of an observation y_{jk} is:

$$(3) \quad f_j(y_{jk} / \mathbf{F}) = \sum_{s=1}^S \mathbf{p}_s f_{j/s}(y_{jk} / \mathbf{b}_s),$$

and the likelihood for \mathbf{F} is:

$$(4) \quad L(\mathbf{F}; y) = \prod_{j=1}^J f_j(y_j / \mathbf{F})$$

where y_j is the observation vector y of SME j .

An estimate of \mathbf{F} , the set of parameters that identifies the segments to which the SMEs belong, and the regression functions within segments, is obtained by maximizing the likelihood of (4) with respect to \mathbf{F} subject to $\mathbf{p}_s > 0$ and $\sum_{s=1}^S \mathbf{p}_s = 1$.

Method

Sample and Data Collection Procedure

To effectively show the merits of the proposed model a context was needed in which there are different types of companies operating in a competitive environment and that have only one alternative to hedge their risks. Moreover, the companies should be within one industry, such that their heterogeneity is not caused by belonging to a different industry. The Dutch pork industry was found to meet all these requirements. In the Dutch pork industry, wholesalers collect hogs from hog farms and then sell them to meat processors, which are slaughterhouses that prepare and pack the meat. The Dutch pork industry is among the largest exporters in the European Union and accounts for an important part of Dutch exports. In contrast with markets for other food products, the pork market in the European Union is free from government intervention. Hog slaughter prices fluctuate widely (Based on daily observations over the period 1990-97, the coefficient of variation (CV) is 0.19.). Even when compared to the prices of US soybeans (The CV is 0.14.), which is generally considered to be a risky commodity, the Dutch hog prices are highly volatile. In this industry there is only one risk management tool type available: the hog futures contract traded at the Amsterdam Exchanges and the pork bellies futures traded at the Chicago Mercantile Exchange. The Dutch hog industry consists of 20,000 producers, 150 hog wholesalers and 65 processors. A sample was randomly drawn from directories kept by the Dutch Agricultural Association for hog farms, the Dutch Union of Livestock Wholesalers, and the Dutch Pork Association for the processors.

A total of 335 producers, 50 wholesalers and 30 processors were interviewed. A personal computer-guided interview was developed and 30 test interviews were conducted to ensure that the questions were interpreted correctly. The interviews took place at the manager's enterprise

and were conducted during the first half of 1998. The managers worked through several assignments and questions, and interviews lasted about 35 minutes. We were also able to obtain accounting data from these 415 firms for the fiscal year 1997 and hence were in the fortunate position to combine accounting data with survey data. Table 1 provides some insight into the size of the companies and their use of derivatives.

Table 1 **Descriptive Statistics of Sample**

	Average number of employees	Average sales	Percent using futures
Producers	3	\$185,000	20%
Wholesalers	7	\$925,000	45%
Processors	60	\$8,100,000	60%

Measures

Dependent variable

The use of derivatives. The use of derivatives was based on past market activity, counting the average underlying value of the number of contracts traded in the last three years.⁸ This measure is in line with Chorafas and Steinmann (1994); and Gunther and Siems (1995) who make use of the notional value of derivatives to reflect involvement in derivative markets. In our sample the only relevant type of derivative was a futures contract, the hog futures contract traded at the Amsterdam Exchanges and the pork bellies futures contracts traded at the Chicago Mercantile Exchange.

Independent variables

Risk Attitude. We used the expected utility model in order to derive the manager's risk attitude (Von Neumann and Morgenstern 1947). Decision making under risk is modeled as a choice between alternatives, in which each alternative is represented by a probability distribution. Decision-makers are assumed to have a preference ordering defined over the probability distributions. In the presence of several preference ordering axioms (Fishburn 1983, 1988), risky alternatives can be ordered using the utility function, $u(x)$. In this model, the curvature of the utility function $u(x)$ reflects risk attitude (Keeney and Raiffa 1976; Pennings and Smidts 2000; Smidts 1997), and the well-known Pratt-Arrow coefficient of risk aversion defined on $u(x)$ provide a quantitative measure of risk attitude.

The utility function $u(x)$ is assessed by means of the certainty equivalence method (cf. Smidts 1997; Keeney and Raiffa 1976). In the certainty equivalence method the respondent compares a certain outcome with the lottery $(x_l, p; x_h)$, where $(x_l, p; x_h)$ is the two-outcome lottery that assigns probability p to outcome x_l and probability $1-p$ to outcome x_h , with $x_l < x_h$. The certain outcome is

⁸ Because we have accounting and survey data, we were able to distinguish between derivative use for speculative and for risk management reasons. Our measure exclusively reflects derivative usage in a hedging context.

varied until the respondent reveals indifference, and is denoted by $CE(p)$. By application of the Von Neumann-Morgenstern utility u we obtain: $u(CE(p)) = pu(x_l) + (1-p)u(x_h)$. Based on the assessed utility curve, the Pratt-Arrow coefficient of absolute risk aversion was derived as a measure of risk attitude (cf. Smidts 1997). The widely used exponential function was fit to each manager's outcomes; after having scaled the boundaries of the functions, the estimation of just one parameter suffices to characterize a decision-maker's risk attitude.⁹ Since it is the certainty equivalents and not the utility levels that are measured with error, the inverse function is estimated (see Appendix for the estimation procedure).

When designing the risk attitude elicitation task for the managers, we used the findings of previous research regarding the sources of bias in assessment procedures for utility functions (Tversky, Sattath, and Slovic 1988). In line with Hershey, Kunreuther, and Schoemaker (1982); and Hershey and Schoemaker (1985), we believe that the main sources of bias are due to the fact that often the experiment does not match the subject's real decision situation. We describe the procedure conducted for the producers and the wholesalers. Our subjects have two choices in selling hogs: take a fixed-price contract or sell the hogs in the volatile spot market, for which they have well-articulated preferences (Payne 1997, Shapira 1997). This decision context closely resembles the certainty equivalence method (Farquhar 1984; Pennings and Smidts 2000; Smidts 1997). An important research design issue involves the dimensions of the lottery. Specifically, what probability and outcome levels should one use in eliciting risk preferences? Since it has been argued in the financial literature that prices follow a random walk path, we chose a probability of 0.5 expressing this random walk (prices can go up or down with equal probability) (Cargill and Rausser 1975; Kendall 1953; Working 1934). The lottery technique was computerized. The first lottery presented to the respondents was a 50/50 lottery with outcomes of 2.34 Dutch Guilders and 4.29 Dutch Guilders chosen as boundaries. The minimum and maximum boundaries for the price of hogs were based on historical data. For each lottery, the manager had to assess the fixed price (i.e. the certainty equivalent) by choosing A (a relatively high price or a relatively low price with a 50/50 chance) or B (a fixed price) over and over until (s)he chose C (indifference towards alternatives A and B), after which a new lottery would start. The assessment of the certainty equivalent was an iterative process. The same procedure was adopted with the processors to elicit their risk attitude, with the exception that we now focused on buying hogs, thus closely matching their daily purchasing decisions.

Risk Perception. Risk perception is measured by means of a scale consisting of a number of statements (multi-item measurement). The scale measures the extent to which the industry member perceives the market in which (s)he operates as risky (see Appendix for a detailed description of the scale). The composite reliability is 0.72 indicating a reliable construct measurement (Hair et al. 1998).¹⁰

⁹ The power function and the exponential function were fit to the data because of their theoretical properties regarding absolute and proportional risk aversion (Tsiang 1972). Since the exponential function fits the data slightly better than the power function, we use the risk attitude measures obtained from the exponential function.

¹⁰ Reliability refers to the extent to which a variable or set of variables is consistent with what it is intended to measure. The value of the construct reliability ranges between 0 and 1, with higher values indicating higher reliability (see Hair et al. (1998) for the calculation of this measure).

Risk Exposure. Risk exposure is measured by the SME's annual number of market transactions in the cash market to sell (buy) his or her output (input). Risk exposure decreases (increases) as the number of market transactions increases (decreases).

Leverage. The leverage is measured by the firm's debt-to-asset ratio.

Size of the Firm. The size of the firm is measured by the firm's annual sales.

Decision-Making Unit. The influence of the DMU is measured by asking a manager to indicate the extent to which significant persons surrounding him/her thought that he/she should use derivatives. The manager was asked to distribute 100 points between using or not using derivatives as a hedging mechanism to reflect the influence of the DMU (Van den Putte, Hoogstraten, and Meertens 1996).¹¹

Level of Education. The level of education is measured on a 5-point scale using the five education levels in the Dutch school system. This 5-level system ranges from the high school to the University level.

Method of Analysis

The parameters of the mixture model can be estimated using the method of moments or using maximum likelihood (Basford and McLachlan 1985; Hasselblad 1969; Quandt and Ramsey 1978). Since maximum likelihood has been shown to be superior for the estimation of the mixture, we use this method to estimate the parameters of the model in (4) (cf. Fryer and Robertson 1972; Wedel and DeSarbo 1995). The likelihood function is maximized using the iterative EM-algorithm (Redner and Walker 1984; Titterington 1990).

The EM algorithm is based on the notion that the likelihood function contains missing observations, i.e. the 0/1 membership of subjects in the s segments. If these were known, maximization of the likelihood would be straightforward. Based on a multinomial distribution for segment membership, the expectation of the likelihood can be formulated. This involves calculating the posterior membership probabilities according to Bayes rule and the current parameter estimates of \mathbf{F} and substituting them into the likelihood. Once this is accomplished, the likelihood can be maximized.

To derive the EM algorithm, we introduce non-observed data, z_{sj} , indicating if SME j belongs to latent segment s : $z_{sj} = 1$ if j comes from segment s , and $z_{sj} = 0$ otherwise. It is assumed that z_{sj} are i.i.d. multinomial:

$$(5) \quad f(z_j | \mathbf{p}) = \sum_{s=1}^S \mathbf{p}_s^{z_{sj}}$$

¹¹ Van den Putte, Hoogstraten, and Meertens (1996) showed that distributing 100 points between using or not using derivatives as a hedging tool provides an accurate measure by forcing respondents to make the trade-off between using derivatives or not.

where the vector $z_j = (z_{sj}, \dots, z_{sj})'$. We denote the matrix $(z_1, \dots, z_j)'$ by \mathbf{Z} and the matrix of explanatory variables (X_1, \dots, X_p) by \mathbf{X} . We assume that y_{jk} given z_j are conditionally independent, and that y_{jk} given z_j has the density:

$$(6) \quad f(y_{jk} / z_j) = \sum_{s=1}^S f_{jk/s}(y_{jk} / \mathbf{b}_s)^{z_{sj}}.$$

With z_{sj} considered as missing data, the log-likelihood function for the complete \mathbf{X} and \mathbf{Z} can be formulated now as:

$$(7) \quad \ln L_c(\mathbf{F}; y, \mathbf{Z}) = \sum_{j=1}^J \sum_{k=1}^K \sum_{s=1}^S z_{sj} \ln f_{jk/s}(y_{jk} / \mathbf{b}_s) + \sum_{j=1}^J \sum_{k=1}^K \sum_{s=1}^S z_{sj} \ln \mathbf{p}_s.$$

This complete log-likelihood is maximized using the iterative EM algorithm. In the E step the log-likelihood is replaced by its expectation, calculated on the basis of provisional estimates of \mathbf{F} . In the M step, the expectation of $\ln L_c$ is maximized with respect to \mathbf{F} to obtain new provisional estimates. The E and M steps are alternated until convergence (a detailed description of this procedure is given by Wedel and Kamakura (1998)).

The actual number of segments is unknown and must be inferred from the model. We use Bozdogan's (1987) Consistent Akaike's Information Criteria (CIAC) to determine the number of segments. The CAIC is defined as:

$$(8) \quad CIAC = -2 \ln L + (P \cdot S + S - 1)(\ln(J) + 1).$$

The number of segments that best represents the data is determined when the CAIC reaches a minimum.

For any set of segments, an Entropy statistic, E_s , can be calculated to assess whether the segments are well separated or defined. E_s is defined as:

$$(9) \quad E_s = 1 - \sum_{j=1}^J \sum_{s=1}^S -\mathbf{a}_{js} \ln \mathbf{a}_{js} / J$$

where \mathbf{a}_{sj} is the posterior probability that SME j comes from latent segment s . The posterior probability can be calculated for each observation vector y_j with an estimate of \mathbf{F} (e.g. Equation (4)) by means of Bayes' Theorem and is given by:

$$(10) \quad \mathbf{a}_{sj}(y_j, \mathbf{F}) = \frac{\mathbf{p}_s \prod_{k=1}^K f_{jk/s}(y_{jk} / \mathbf{b}_s)}{\sum_{s=1}^S \mathbf{p}_s \prod_{k=1}^K f_{jk/s}(y_{jk} / \mathbf{b}_s)}.$$

The entropy statistic E_s in (9) is a relative measure, bounded between 0 and 1, and describes the degree of separation in the estimated posterior probabilities. E_s values close to 1 indicate that the posteriors probabilities of the respondents belonging to specific segments are close to either 0 or 1; the segments are well defined.¹² E_s values close to 0 indicate that the segments are not well defined.

¹² In the case where only one segment is used, E_s is trivially 1.

Results

The estimated parameters in our model are distributed asymptotically normal (DeSarbo and Cron 1988), and we assume that \mathbf{F} is identifiable. Titterton, Smith, and Makov (1985) have shown that mixtures of distributions in the exponential family are generally identified. An exception occurs when there exists a high degree of collinearity in the \mathbf{X} matrix of the explanatory variables. In this study we assessed collinearity by investigating the squared multiple correlations coefficient, R_x^2 between x_x and the other set of P explanatory variables. Using Klein's rule, we found that $R_y^2 > R_x^2$ where R_y^2 is the squared multiple correlation between y and the explanatory variables (Klein 1962), thereby indicating that the assumption of limited collinearity is tenable. Moreover, the correlation between the explanatory variables is insignificant ($p < 0.025$). Another potential problem associated with the application of the EM algorithm to mixture models is its convergence to local maximum. To overcome this problem we started the algorithm from a wide range of starting values as suggested by McLachlan and Basford (1988).

We now investigate whether it is appropriate to treat all managers in a similar way or whether segments of managers exist that exhibit different derivative use behavior. To clarify the benefits of considering various segments, the effect of the managers' and firms' characteristics on derivative usage was first estimated treating all managers as one segment (i.e., $S = 1$). The results are presented in Table 2.

Table 2 Aggregate Mixture Regression Parameter Estimates

	Regression coefficient
Risk exposure ¹	-0.104*
Size of firm	0.017*
Influence of DMU	0.102*
Leverage	0.021
Risk attitude (RA)	0.052
Risk perception (RP)	0.016
Interaction ² (RP*RA)	0.210*
Level of education	0.049
<i>Log-likelihood</i>	-1190
<i>CIAC</i>	2449
<i>R-square</i>	0.06

¹Risk exposure declines as the number of market transactions increases, hence the negative sign.

²The risk perception and risk attitude variables were centered prior to forming the multiplicative term (Cronbach 1987; Jaccard, Turrissi, and Wan 1990).

* denotes $p < 0.05$.

The solution has a log likelihood of -1190 and an R^2 of 0.06 . From Table 2 it appears that the level of risk exposure, size of the firm and the influence of the decision-making unit are significantly positively related to derivative use, which is consistent with Géczy, Minton, and Schrand (1997); and Carter and Sinkey (1998). Interestingly, the decision-making unit, often

neglected in research, has a significant influence on the use of derivatives. Although managers of SMEs make decisions ultimately on their own regarding derivative usage, they are influenced by people in their DMU. Consequently, it would seem valuable for financial institutions to target their marketing efforts not only on the manager, but also on their consultants and bank account managers. Surprisingly, the fundamental determinants behind risk management, risk attitude, risk perception, are not significantly related to derivative usage, but the interaction between the two is. This supports the notion that the interaction between risk attitude and risks perception is an important driving force behind risk management behavior and that risk attitude links risk perception to behavior as reflected in the interaction. The firm's leverage is not significantly related to derivative usage, a finding that is confirmed by Mian (1996), nor is the level of education significantly related to derivative usage.

Because we expect that there might be latent segments in our sample, the mixture regression model was applied to the data for $S = 1$ to $S = 6$. The log-likelihoods, corresponding CIAC, and the Entropy E_s and R-square statistics of this analysis are listed in Table 3.

Table 3 Fit Statistics of the Mixture Models for a Different Number of segments

Segments S	Log likelihood	CIAC	E_s	R-square
1	-1190	2449	1.00	0.058
2	-862	1850	0.80	0.454
3	-840	1841	0.77	0.481
4	-839	1920	0.51	0.480
5	-838	1977	0.42	0.482
6	-835	2024	0.41	0.491

CIAC is the Consistent Akaike's Information Criteria; E_s is the entropy statistic.

Based on the minimum CIAC statistic, we select $S = 3$ as the appropriate number of segments. The solution has a log likelihood of -840 and an R^2 of 0.48. Table 4 presents the estimated coefficient for this three-segment solution.

The entropy value of 0.77 indicates that the mixture components are well separated or defined, i.e. the posteriors are close to 1 or 0. The R-square has significantly improved from 0.06 for the aggregate regression model ($S = 1$), to 0.48 for the three-segment solution.

Table 4 Mixture Regression Results for the Three Segment Solution

	Regression coefficients		
	$s = 1$	$s = 2$	$s = 3$
Risk exposure ¹	-0.170*	-0.088*	-0.176
Size of firm	0.550**	0.187*	0.326
Influence of DMU	0.458**	0.017	0.254*
Leverage	0.031	0.033	0.201*
Risk attitude (RA)	0.017	0.054	0.668*
Risk perception (RP)	0.072*	0.016	0.471**
Interaction ² (RP*RA)	0.220*	0.042	0.452*
Level of education	0.042	0.112*	0.832**
Relative Segment Size p	0.44	0.30	0.26
Percentage of Channel Member Type in Segment			
Producers	49%	29%	22%
Wholesalers	36%	42%	22%
Processors	4%	20%	76%

¹Risk exposure decreases as the number of market transactions increases, hence the negative sign.

²The risk perception and risk attitude variables were centered prior to forming the multiplicative term (Cronbach 1987; Jaccard, Turrisi, and Wan 1990).

* denotes $p < 0.05$; ** denotes $p < 0.01$.

In the first segment, consisting of 44% of the total sample, risk exposure, size of firm, the influence of the DMU and the manager's risk perception show a significant association with the use of derivatives. These findings confirm the previous findings of Carter and Sinkey (1998); Géczy, Minton, and Schrand (1997); and Nance, Smith, and Smithson (1993). Moreover, the interaction between risk attitude and risk perception is significantly associated with derivative usage. Compared to the other two segments this segment uses the least derivatives. Segment 1 ($s = 1$) contains 49% of the producers, 36% of the wholesalers and 4% of the processors.¹³ The second segment ($s = 2$) consists of 30% of the sample, and shows significant effects of risk exposure, size of firm, and level of education. In this segment, the use of derivatives is modest, more than in Segment 1 but less as in Segment 3 ($s = 3$). This segment contains 29% of the producers, 42% of the wholesalers and 20% of the processors. In this segment the fundamental determinants, risk attitude and risk perception and their interaction, are not significantly related to derivative usage. In contrast, risk perception, risk attitude and their interaction are significantly related to derivative usage in Segment 3. The terms can be clearly interpreted: A risk-averse manager will use relatively more derivatives in order to reduce price risk. When the manager perceives a large price risk (i.e. high-risk perception), using derivatives will be more prominent. A risk-averse manager, with high-risk perception will result in a heavier reliance on derivatives. Moreover, other financial determinants such as leverage are significantly related to derivative use in this segment. Also, the level of education, and the influence of the DMU are

¹³ While about 90% (164 out of 183) of segment 1 is composed of producers, producers are an important part of the other segments as well.

significantly related to derivative use. Segment 3 is the smallest segment, containing 26% of the sample and 22% of the producers, 22% of the wholesalers and 76% of the processors. The results of our study demonstrate the existence of multiple industry segments with different relationships between managers' and firms' characteristics and derivative use.

To profile more comprehensively our managers we posed several questions regarding derivatives and markets in the form of 7-point Likert statements (Westermann 1983). We asked managers to identify the extent to which: a) they use risk spreading techniques, e.g., sell to more than one buyer, (1 = no use of techniques, and 7 = extensive use of techniques); b) derivatives yield good prices, (1 = yield very bad prices, and 7 = yield very good prices); c) they follow market prices, (1 = do not follow, and 7 = follow very closely); d) derivatives are able to reduce price risk, (1 = not at all, and 7 = able to eliminate price risk); and e) derivatives are easy to use, (1 = not easy at all, and 7 = very easy to use). Next, we classified the managers into our three segments so that membership reflected a manager's highest posterior probability of belonging to a particular segment based on (10).

Table 5 tabulates the responses to the additional questions for the three segments.

Table 5 Profile of the Three Segments

	<i>s</i> = 1		<i>s</i> = 2		<i>s</i> = 3	
	Mean	SD	Mean	SD	Mean	SD
Age	42	9.8	42	8.7	43	10.1
Using risk spreading activities	3	1.5	4	1.4	5	1.4
Derivatives yield good prices	2	1.4	4	1.6	3	1.7
Follow the market prices closely	3	1.3	4	1.2	6	1.2
Risk reduction performance	2	1.4	4	1.3	5	1.1
Ease of use	3	1.7	5	1.4	6	1.2

SD is the standard deviation.

The first segment is characterized by respondents who do not use risk spreading techniques extensively, and who believe that derivatives do not yield good prices and perform poorly at reducing price risk. This group finds derivatives rather difficult to understand and does not follow market prices extensively. This segment can be described as “focusing on production rather than on marketing their products” which further explains the relative low use of derivatives. This orientation also helps to explain why the DMU is so important in this segment (see Table 4). These managers appear to rely heavily on the expertise of consultants or bank account managers when the use of derivatives is concerned. Further, these managers, who are not heavily involved in the use of derivatives as a hedging tool, might not be well informed about derivatives, which is consistent with the fact that this segment had the lowest education level.

Managers who think that derivatives are easy to use but are neutral regarding their risk reduction and pricing performance describe the second segment. In this segment risk management behavior is not driven by their risk attitude and risk perception. The third segment has a rather positive attitude towards derivative usage. Managers believe that derivatives are able to reduce risk, but are neutral regarding whether derivatives produce high prices. It appears that this segment uses derivatives as a hedging tool, not to receive high prices. Managers in this segment follow market prices closely which might explain the influence of the interaction term

between their perceived risk and risk attitude on derivative use. This segment seems to use “financial structure” characteristics (as imbedded in the debt-to-asset ratio, risk attitude and risk perception) in their decision to engage in derivatives. In addition, the DMU is a determinant significantly associated with derivative usage.

Discussion

Our analysis of the determinants of derivative usage in the Dutch hog industry revealed the presence of multiple segments that can be interpreted on the basis of existing theory of hedging behavior. Risk exposure, size of firm, the firm’s decision unit, leverage, risk attitude, risk perception, the interaction between risk attitude and risk perception and level of education, are factors related to derivative usage. However these factors are not equally important throughout the industry. Assuming homogeneity in managers’ responses and fitting a pooled model yielded a modest fit, and the conclusion that only risk exposure, size of firm, the manager’s decision making-unit and the interaction between risk attitude and risk perception are determinants of SMEs derivative usage. Allowing for heterogeneity in managers responses increased the model fit dramatically. More importantly, it demonstrated that the importance of the determinants varied significantly across the segments. The heterogeneity at the segment level appears to have masked significant effects at the aggregate level, notably the effects of risk attitude, risk perception, leverage, and the manager’s level of education.

The fact that the heterogeneity is not based on observable variables such as age or region, but rather is unobservable and imbedded in the determinants that influence the derivative decision. In order to identify these unobserved segments, procedures must be used that simultaneously identify the determinants of derivative usage and the segments based on these determinants. In this paper we introduce a mixture model that is able to provide the probability that each SME belongs to the derived segments, and regression coefficients in each respective segment, which relate derivative usage to the explanatory variables. The importance of accounting for heterogeneity is further substantiated by fact that we studied derivative usage within one industry (e.g., the Dutch hog industry). We would expect that studying derivative usage across industries would reinforce our conclusion that unobserved heterogeneity must be considered.

Our work has at least two implications for financial institutions. First, the heterogeneity of derivative usage suggests that financial institutions need to use different tools to attract different segments. Identifying the different segments is a challenge. With this information, the financial institution is able to target their marketing efforts and design customized financial products. Angel, Gastineau, and Weber (1997); Fridson (1992); Nesbitt and Reynolds (1997) show the importance of customizing financial services. Based on the characteristics of the different segments, financial institutions can select a group of potential customers, to whom they offer risk reduction services designed to match the customer’s derivatives use profile. This implies differentiation of services offered by financial institutions. In our empirical study, the segments are not be easily observed by the financial institutions, i.e., we found unobserved heterogeneity. In this regard the proposed mixture model is a valuable tool as it detects unobserved

heterogeneity, and helps to identify these unobserved segments.¹⁴ Having identified the segments and having gained information about the segment's profile the financial institution is able to target these segments and to design securities that better fit to the segment's needs. Second, the importance of the DMU in derivative use decisions suggests that managers of SMEs rely heavily on the expertise and advice of consultants and bank managers. Hence, the use of derivatives among SMEs can be stimulated through targeted programs that promote the advantages of derivatives to the members of these support groups.

In this study risk perception was measured with a self-report scale, thereby lacking the advantages of a revealed preference methods that were used to elicit risk attitude. Using a risk perception revealed preference method, such that the respondent's cumulative probability distribution function is elicited (e.g., Farquhar 1984; Jia, Dyer, and Butler 1990), would further enhance our measurement of risk perception and the interaction between risk perception and risk attitude and likely would reinforce our conclusion that they are important variables in understanding derivative usage.

The mixture model framework can be applied to other areas in the finance literature where heterogeneity is an issue. For example, research on investor's disposition of assets has demonstrated a tendency of investors to hold losing investments too long, and to sell profitable investments too soon. The use of the mixture model presented here on a sample of investors could reveal segments of investors with different levels of disposition, and identify the factors or characteristics influencing the behavior of the investors in each segment (e.g., Odean 1998). Further, research has not yet addressed adequately investors' heterogeneous response to similar information. The use of a mixture framework could reveal groups of investors, and their characteristics, on the basis of the way they respond to and hence process information. This in turn would increase our insights into market reactions triggered by new information (e.g., King 1991; Kryzanowski and Zhang 1996; Hirshleifer, Subrahmanyam, and Titman 1994). The use of mixture models in these and other analyses will expand our understanding of the detail workings of financial and commodity markets.

¹⁴ We examined three different channel members: producers, wholesalers, and processors. A priori, one might have expected that segments in the industry would have been identified by these business categories. However, our empirical analysis indicates that that producers, wholesalers, and processors are spread across the three segments. This finding indicates that the type of firm (which can be observed) is not necessarily a strong predictor of derivative usage, but rather that the decision making process (which is unobserved), as reflected in the regression coefficients of each segment, is a strong predictor of derivative usage.

Appendix. Estimation of Risk Attitude Based on the Manager's Responses

The exponential utility function was fit to each manager's responses using 9 observations. The exponential utility function $u(x)$ can be written as:

$$(A.1) \quad U(x_i) = \frac{1 - e^{-a(x_i - x_L)}}{1 - e^{-a(x_H - x_L)}}.$$

In equation (A.1) x_L and x_H represent the lower and upper bounds of the selected outcome range. The parameter a is the Pratt-Arrow coefficient of absolute risk aversion. If $a > 0$ the manager is risk averse; if $a < 0$ the manager is risk seeking. Since the certainty equivalents, and not the utility levels, are measured with error, an inverse function of (A.1) is estimated. Following Smidts (1997), the inverse estimation function is:

$$(A.2) \quad x_i = \frac{\ln(0.5(e^{-ax_l} + e^{-ax_h}))}{-a} + e_i.$$

In equation (A.2) x_l and x_h represent the low and high outcomes of the 50/50 lottery, e_i indicates the response error and x_i is the assessed certainty equivalent. The respondent assesses x_i for nine lotteries with varying x_l and x_h . The parameter a in (A.2) is estimated using routine ZXMIN from the IMSL-library of FORTRAN programs. In ZXMIN the Fletcher's Quasi-Newton Method is used to obtain the least squares estimate.

Description of the Risk Perception Scale

To examine the measurement quality of the constructs confirmatory factor analysis was performed using LISREL 8 (Jöreskog and Sörbom 1993).

SMEs were asked to indicate their agreement with the following items using a 9-point scale that ranged from "strongly disagree" to "strongly agree":

- 1) I am able to predict hog prices.
- 2) The hog market is not at all risky.
- 3) I am exposed to a large amount of risk when I buy/sell hogs.

The value of the construct reliability, which ranges between 0 and 1 (with higher values indicating higher reliability (see Hair et al. 1998), was 0.72.

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